On Your Social Network De-anonymizablity: Quantification and Large Scale Evaluation with Seed Knowledge

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Princeton University





Outline

- Introduction and Motivation
- System Model
- De-anonymization Quantification
- Evaluation and Observations
- Conclusion and Future Works





Structured/Graph Data





- Structured/Graph Data
 - Social Networks





- Structured/Graph Data
 - Social Networks
 - Mobility Traces



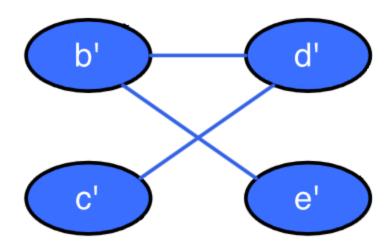


- Structured/Graph Data
 - Social Networks
 - Mobility Traces
 - Email Networks





The Anonymized Graph (e.g. Facebook)

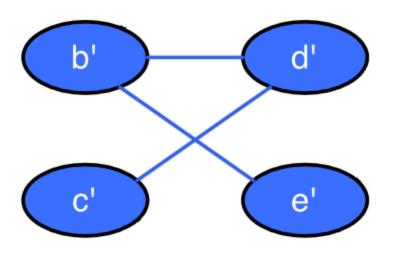


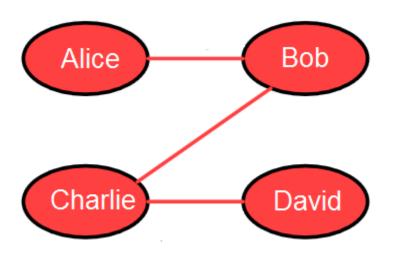




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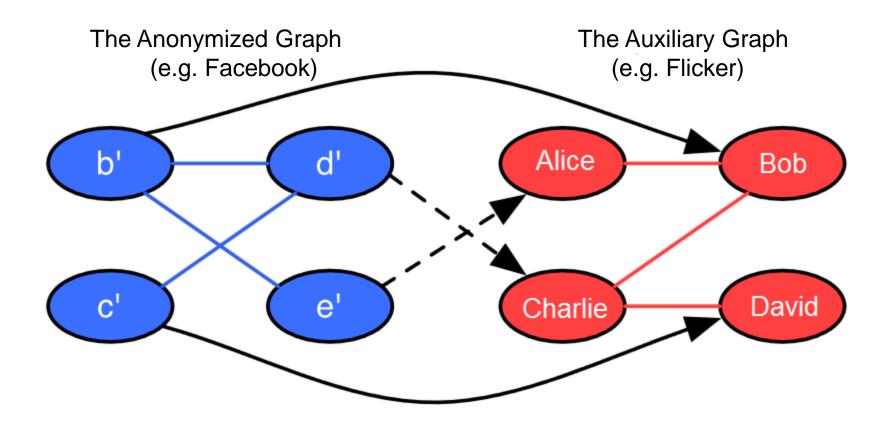
The Auxiliary Graph (e.g. Flicker)













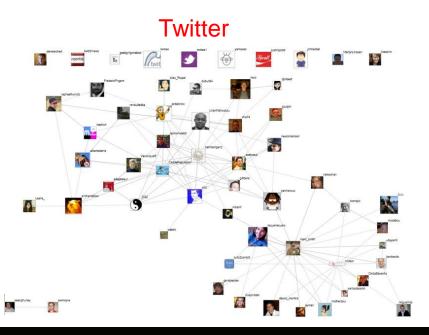


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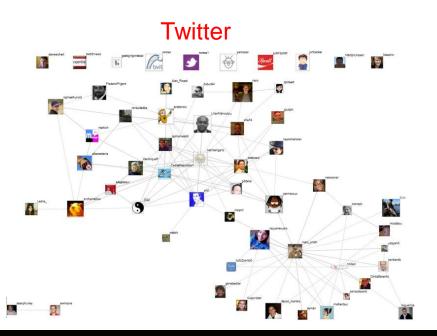


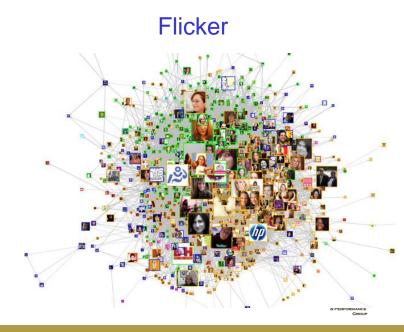
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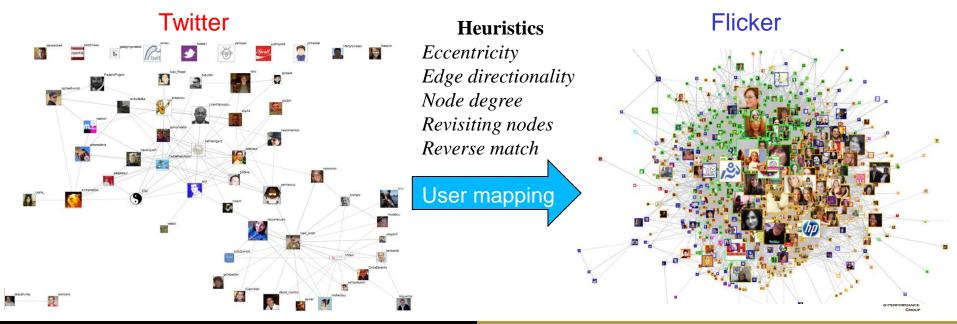


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 - 3.3M users, 53M edges
- Result: 30.8% of the users are successfully de-anonymized



Motivation

• Question 1: Why social networks are vulnerable to structure based de-anonymization attacks?





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- Question 2: How de-anonymizable a social network is?





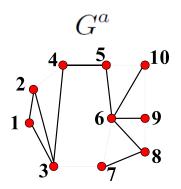
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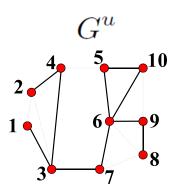
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- Question 2: How de-anonymizable a social network is?
- Question 3: How many users within a social network can be successfully de-anonymized?





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- Auxiliary Data (G^u)

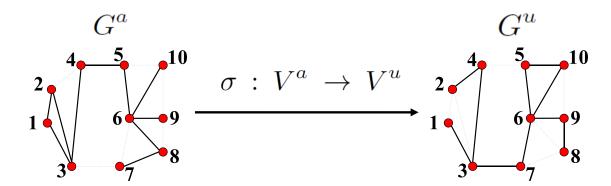








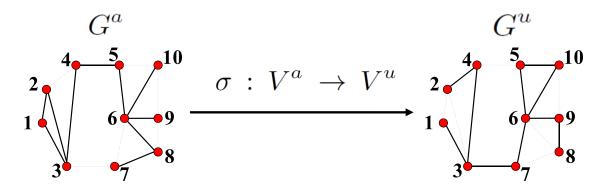
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- De-anonymization (σ)







- Anonymized Data (G^a)
- Auxiliary Data (G^u)
- De-anonymization (σ)
- Measurement(Δ_{σ})



De-anonymization Error (DE) on a user mapping $(i, i') \in \sigma$

$$\Delta_{\sigma:(i,j)}(s) = \left|\sigma \left(E_i^a(S^a)\right) \backslash E_j^u(S^u)\right| + \left|\sigma^{-1} \left(E_j^u(S^u)\right) \backslash E_i^a(S^a)\right|$$

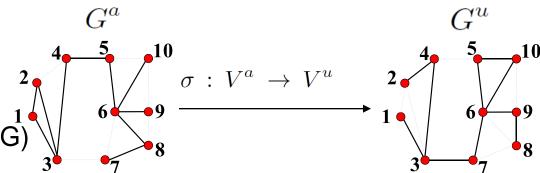
$$\Delta_{\sigma}(S) = \sum_{(i,j)\in\sigma} \Delta_{\sigma:(i,j)}(S)$$





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- Auxiliary Data (G^u)
- De-anonymization (σ)

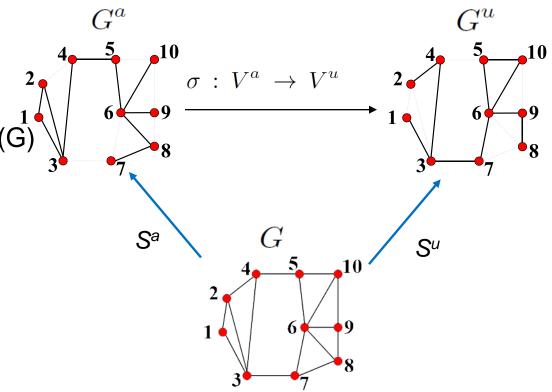
Conceptual Underlying Graph (0)







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- Auxiliary Data (G^u)
- De-anonymization (σ)
- Conceptual Underlying Graph (G)







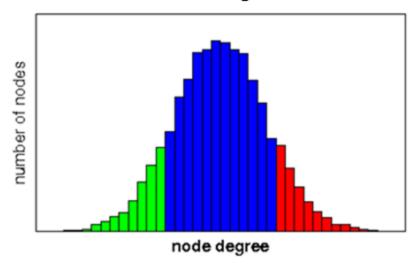
- Conceptual Underlying Graph:
 - Erdős–Rényi(ER) model





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The ER Model Degree Distribution

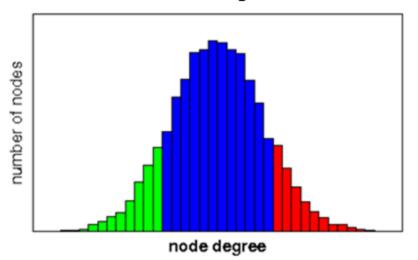




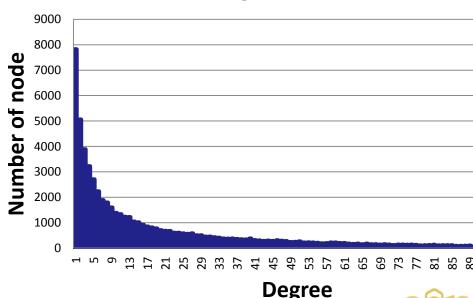


- Conceptual Underlying Graph:
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The ER Model Degree Distribution



Facebook Degree Distribution





- Conceptual Underlying Graph:
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 - General model





- Conceptual Underlying Graph:
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- Quantifications
 - Mathematically shown the conditions needed





- Conceptual Underlying Graph:
 - Erdős–Rényi(ER) model
 - General model
- Quantifications
 - Mathematically shown the conditions needed
 - Seed based perfect de-anonymization
 - Structure based perfect de-anonymization
 - Error tolerant de-anonymization





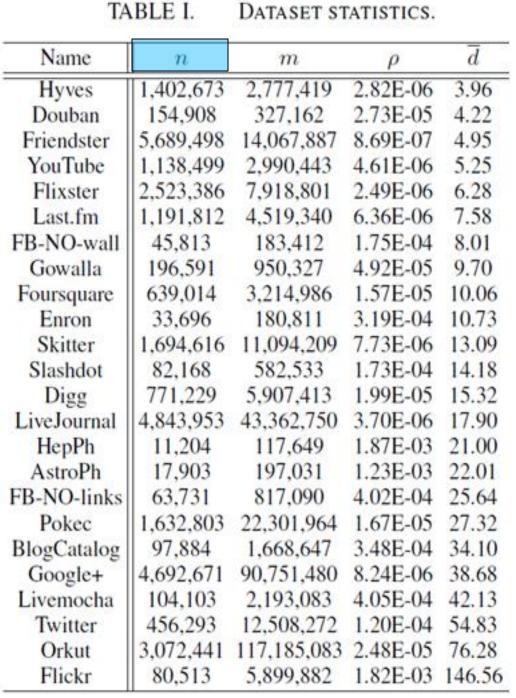
Datasets



Name	n	m	ρ	\overline{d}
Hyves	1,402,673	2,777,419	2.82E-06	3.96
Douban	154,908	327,162	2.73E-05	4.22
Friendster	5,689,498	14,067,887	8.69E-07	4.95
YouTube	1,138,499	2,990,443	4.61E-06	5.25
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- Number of nodes (n)
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- Number of edges(m)
- Graph density (ρ)
- Average degree (\bar{d})

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- Datasets Types
 - Social media(e.g. LiveJournal4 million nodes,43 million edges)



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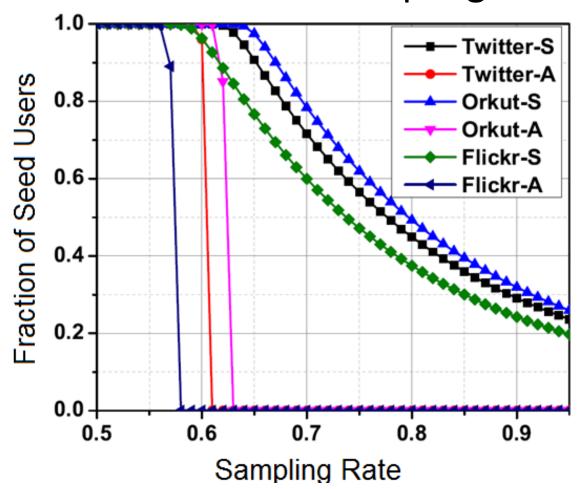
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 - Email network
 (e.g. Enron
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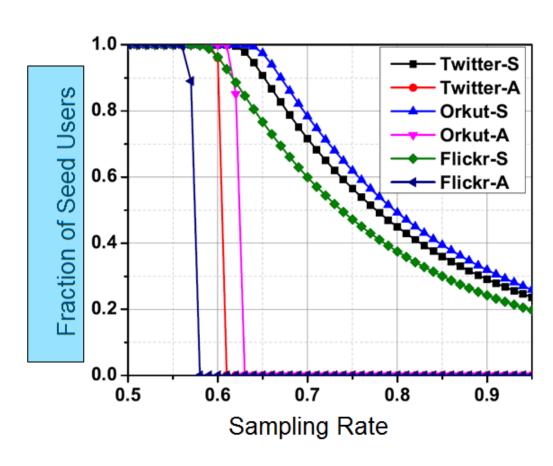
Perfect De-anonymization Analysis on seed users versus sampling rate







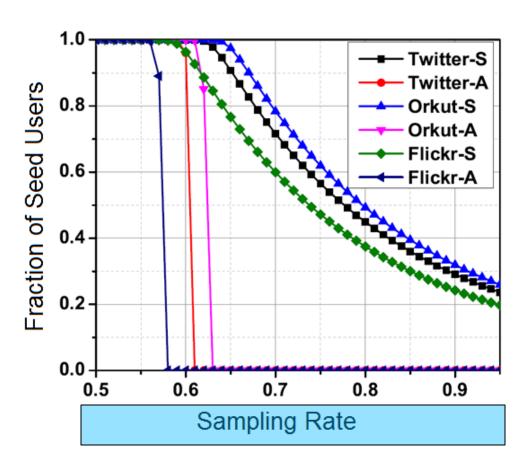
 The y-axis: number of pre-determined users needed.







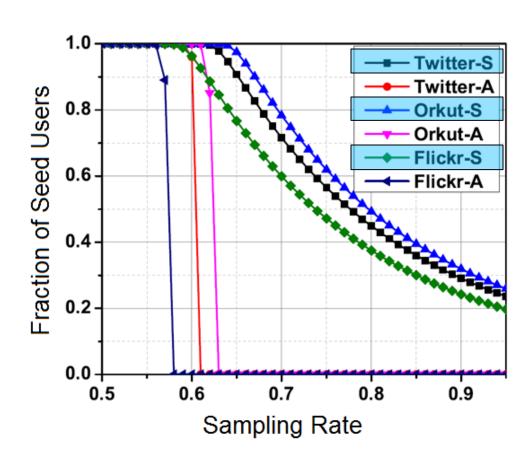
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- The y-axis: number of pre-determined users needed.
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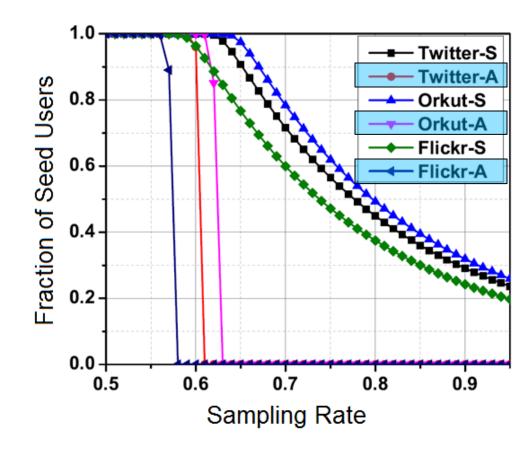






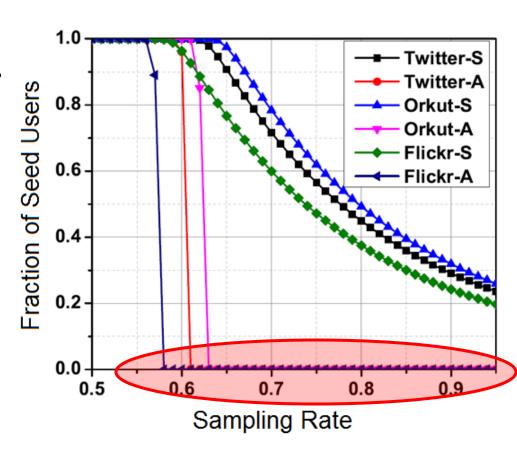
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- *-S: de-anonymization with only seed information.
- *-A: de-anonymization with seed and structural information

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 When sampling rate is large no seeds needed for perfect de-anonymization.

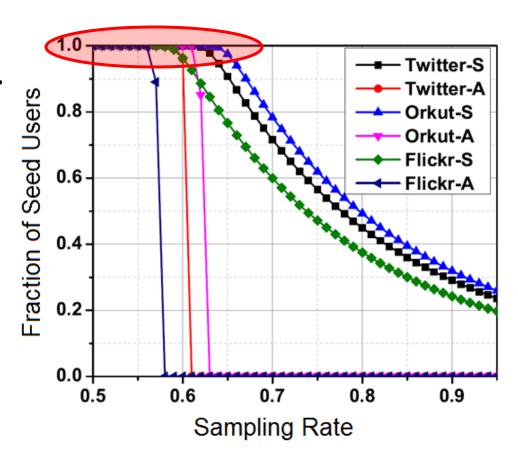






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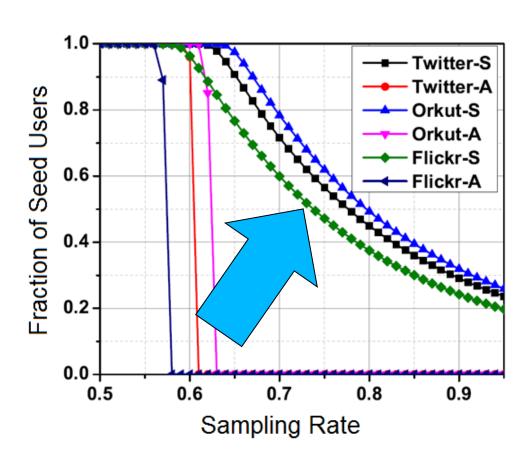
 When sampling rate is small all users need to be seed users for perfect deanonymization.







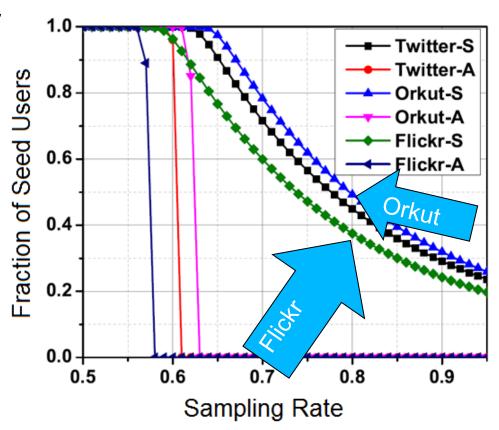
 Using only seed information, fewer seed users are required with lower sampling rate.







- Graphs with higher density requires fewer seed users.
 - Orkut density of 2.48E-5
 - Flicker density of 1.82E-3







Conclusion and Future Works

Conclusion

- Theoretical quantification with no degree distribution requirement.
- Large-scale de-anonymizability evaluation.

Future works

- New mathematical model
- Defense techniques





Thank you!

Questions?

Acknowledgement

We thank the anonymous reviewers very much for their valuable comments!



